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Analysis of English Reading Difficulty Evaluation

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Abstract

Faced with the English version of the literature, some literature are easier to read, while others are difficult to read. If we can know the reading difficulty of an English document, it will help us filter out many materials that are not suitable for reading. In this regard, we decided to filter out some feature values that affect English reading from a large number of texts, such as the proportion of difficult words in the article, the length of sentences, and the proportion of polysyllabic words. We initially use the English test question score as the article difficulty score. First, the sample data is divided into a training set and a test set. For the training set, we calculate the Pearson correlation coefficient between the correct rate of the article and each eigenvalue, and filter out the eigenvalues with small correlation coefficients. Among the remaining eigenvalues, the five eigenvalues, namely, the ratio of symbol-like symbols, the complexity of sentences, the ambiguity of words, the ratio of multi-syllable words, and the proportion of difficult words, are the final screening results. We adopt a comprehensive evaluation model, analyze the eigenvalues by the entropy weight method, and calculate the entropy weight ratio of the above eigenvalues. After knowing the weights, we can predict and score the reading difficulty of English articles. A preliminary English article difficulty prediction model was completed. For the test set, linear regression is used to obtain the residual between the test value and the real value. Through multiple rounds of iteration, the residual is reduced and the fitting is continued, and finally a model that can evaluate the reading difficulty of English text is obtained.

Keywords

Pearson correlation coefficient, English reading, linear regression.

1. Introduction

For readers of different ages and educational levels, how to choose English texts suitable for difficulty has attracted the attention of scholars and experts. For Microsoft Word, we can choose to display information about the reading level of the document, where the readability score for that text is calculated according to the Flesh Reading Ease formula [1-3]. But this model is very sketchy and has a lot of irrationality. So we need to build a model to assess the reading difficulty of English texts we might see in common situations.

As one of the main carriers of information, text is not only growing faster and faster, but its sources and expressions are also becoming more and more diverse and diversified. It is becoming more and more difficult for users to find texts that meet specific needs. Automated means of analyzing and processing text are becoming increasingly important.

We need to build a model to assess the reading difficulty of English texts we might see in common situations in order to use the texts as reading material for language tests at the appropriate level of difficulty. Readability of text generally refers to how easy it is to understand the text[4]. For text readability evaluation, the core problem is to establish the relationship between text features and readability (generally quantified as readability level or score, which includes two important steps: text representation and model learning).

Text representation refers to transforming text into another form of data that makes it easier for a model to process and learn rules from. This representation is also known as a feature. Model learning refers to building a model based on the text of known readability categories to analyze the relationship between text features and categories, and to be able to predict the readability of unknown texts. Since models have their own preferences [5] and text types have their own characteristics, the selection of eigenvalues is particularly important.

Research on automatic measurement of text readability is mainly used to evaluate whether texts can be used as reading materials for language tests of appropriate difficulty levels, and can be divided into academic research value and practical significance. In terms of academic significance, the measurement of text readability provides a research direction for natural language processing [6], which can promote the development of natural language processing related technologies. In terms of practical significance, firstly, automatic and effective measurement of text readability, and secondly, automatic and effective measurement of text readability is particularly important for the accessibility of key information, and also plays a key role in specific application fields. These functions include providing reading materials of suitable difficulty for language learners [7] with different reading abilities, such as the well-known graded reading, which is to recommend extracurricular reading materials of suitable difficulty for language learners at different stages. In addition, it can also be further applied to the precise retrieval and recommendation of web text.

This study carried out the assessment of the difficulty of English reading materials, also known as readability research, that is, the method of applying features combined with neural network learning. Through the comprehensive evaluation model, natural language processing is carried out on the English textbook articles [8-10] and reading materials, and the different dimensional features that affect the readability (difficulty) of the text such as phrases, words, sentences, and paragraphs in the text are extracted. The problem of setting the readability value label is solved by calculating the value of the Pearson correlation coefficient between the article score and many eigenvalues, and the eigenvalues are analyzed and modeled by the entropy weight method. Therefore, this research uses advanced information science statistical methods such as neural network system learning, focusing on the in-depth mining[11] and scientific analysis of multi-dimensional feature data[12].And exploring the implicit relationship between the internal laws of English compilation[13] behind the features to achieve higher quality English reading materials. readability assessment. This research has very important practical significance and application value.

For English texts, some texts are easy to read, while others are very difficult to read. Readable scores according to the Flesch Reading Ease test are undoubtedly a great help for us. However, this test score is not very reliable for us, and we need to use a new method for modeling to evaluate the reading difficulty of our English text in common situations[14]. The establishment of the model should be in line with the understanding of the difficulty of reading articles by most people.

The readability score of the Flesch Reading Ease test is unreasonable. It only considers the average length of the sentence in the article and the average syllable of each word. The selection of eigenvalues is very small and has certain contingency, which cannot strongly support the text. In this regard, our model selects a large number of eigenvalues of the text. In order to ensure the scientificity of the eigenvalue selection, we analyze the closeness between the eigenvalues and the difficulty of the text, and eliminate the eigenvalues with less closeness. Among the remaining eigenvalues, in order to understand which eigenvalue has a greater impact on the difficulty of the text, we use the comprehensive analysis method to analyze the weights to ensure that the selected eigenvalues have an appropriate entropy weight ratio, and finally calculate Score the article.

2. Eigenvalue Selection and Weight Determination

2.1. Eigenvalue Selection.

The study of English readability has always attracted much attention. Different scholars have also given different views on the selection of the characteristic value of reading difficulty. In the Flesch formula, the characteristic value of reading difficulty is the average sentence length and average word length. The Gunning Fog formula selects the average sentence length and the ratio of complex words to measure the reading difficulty of the text; the Coleman-Liau formula selects the word length and the number of sentences to calculate the readability score; the Automated Readability Index selects the grade level, the average number of characters per word, the number of characters per sentence Average number of words as feature value. The American RAND Reading Research Group also put forward its own views on the factors affecting reading difficulty from six aspects: discourse genre, discourse structure, media form, sentence difficulty, content, and texts that have different appeals to different readers. On the basis of summarizing the text readability characteristics studied by the former, this paper selects 11 main factors that affect the difficulty of reading English texts, and builds the following factor framework.

Although these factors have a certain impact on the difficulty of reading, not all factors are easily characterized and simulated, and some even affect the accuracy of model prediction. Experts in this field also believe that when selecting input variables, It does not have to be comprehensive. Therefore, the factors that are most suitable for predicting the difficulty model of English text should be selected.

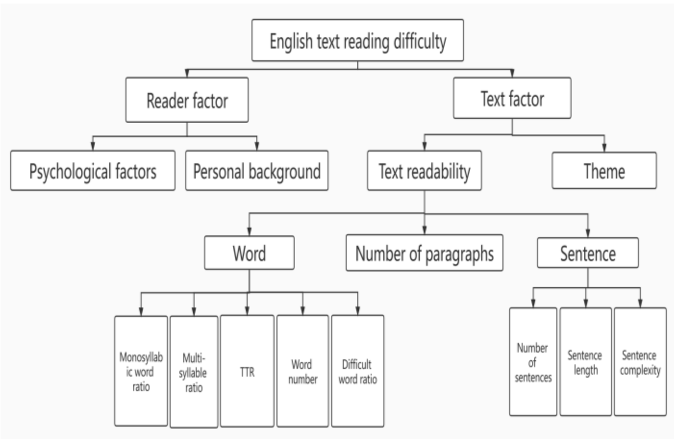

Figure 1:Framework of Factors Affecting English Reading Difficulty

We calculate the Pearson correlation coefficient between the value of each factor and the actual difficulty value,see Fig 1. The Pearson correlation coefficient between two variables is defined as the quotient of the covariance and standard deviation between the two variables:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_{,X}\sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X\sigma_Y} \tag{1}$$

The above formula defines the overall correlation coefficient, and Greek lowercase letters(1)-(3) are commonly used as representative symbols. Estimate the covariance and standard deviation of the sample to get the Pearson correlation coefficient:

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} \tag{2}$$

when the r can also be estimated from the mean value of the standard scores of the sample points, and an expression equivalent to the above equation can be obtained:

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{X_i - \bar{X}}{\sigma_X}\right)\left(\frac{Y_i - \bar{Y}}{\sigma_Y}\right) \quad (3)$$

Observing the above results, we can see that the correlation between the value of each factor and the actual difficulty value is different, and the factors from high to low are: sentence complexity (the correlation coefficient with the actual difficulty value is -0.898); difficult words Proportion (the correlation coefficient with the actual difficulty value is -0.884); the multi-syllable word ratio (the correlation coefficient with the actual difficulty value is -0.802); the symbolic symbol ratio (the correlation coefficient with the actual difficulty value is -0.731); The ambiguity (the correlation coefficient with the actual difficulty value is -0.68); the number of segments (the correlation coefficient with the actual difficulty value is 0.573); the ratio of single syllable words (the correlation coefficient with the actual difficulty value is -0.531); the total number of times (The correlation coefficient with the actual difficulty value is -0.522); the proportion of long sentences (the correlation coefficient with the actual difficulty value is -0.481); the number of sentences (the correlation coefficient with the actual difficulty value is -0.272). The Pearson Correlation Coefficient are shown in Table 1.

Table 1:Some Pearson Correlation Coefficient

	Number of Words	Number of Paragraphs	Proportion of Difficult Words	Number of Sentences
Number of Words	1.000(0.000***)	0.573(0.052)	-0.884(0.000*)	-0.272(0.392)
Number of Paragraphs	-0.522(0.082)	1.000(0.000***)	0.583(0.047*)	0.741(0.006**)
Proportion of Difficult Words	-0.330(0.295)	-0.330(0.295)	1.000(0.000***)	-0.134(0.679)
Number of Sentences	0.583(0.047*)	-0.481(0.114)	-0.481(0.114)	1.000(0.000***)

*p<0.05,**p<0.01,***p<0.001.

For the article subject matter, which affects the difficulty of reading, a one-way analysis of variance method is used to calculate and analyze:

Propose the original hypothesis and alternative hypothesis. The assumption that the original hypothesis is the subject matter has a greater impact on the reading difficulty value than the random error has on the difficulty value:

$$H_0: \ \mu_1 = \mu_2 = \ldots \mu_k \quad (4)$$

The influence of factors on experimental results (4) is less than the influence of random errors on experimental results.If they are not all equal, the influence of factors on the experimental results is greater than the influence of random errors on the experimental results. If the null hypothesis is rejected, it means that the influence of factors on the experimental results is greater than that of random errors. If the null hypothesis is not rejected, there is insufficient evidence to prove that the influence of factors on the experimental results is greater than that of random errors. In particular, when rejecting the null hypothesis, all population means $\mu_1, \mu_2, \ldots, \mu_i, \ldots, \mu_k$, should have at least two population means that are not equal, but there is no guarantee that all population means are not equal at the same time.

Select and construct test statistics. In order to test whether the null hypothesis is true, it is necessary to select an appropriate test statistic and calculate the value of the test statistic. Calculate the mean values of factors at different levels:

Calculate the total mean of all observations:

Among them, in order to construct the test statistic, it is necessary to calculate 3 sums of squares of errors: the sum of squares of total errors (SST), the sum of squares of factor errors (SSA), and the sum of squares of random errors (SSE). The calculation formula is as follows:

Since the size of the three error sums of squares is affected by the number of observations, the larger the number of observations, the larger the calculated error sum of squares. In order to eliminate the influence of the number of observations on the size of the error sum of squares calculation results, it is necessary to divide the calculation results of the square sums by their respective degrees of freedom, that is, the mean square. The three degrees of freedom are: $n-1, k-1$ and $n-k$.

The mean square of SSA is also called the between-group mean square or between-group variance, and is denoted as MSA. The calculation formula can be expressed as MSA = sum of squares between groups/degrees of freedom=SSA/(k-1); the mean square of SSE is also called the mean square within the group or the variance within the group, and is denoted as MSE. The calculation formula is: MSE=sum of squares within a group or degrees of freedom = SSE/(n-k). The statistical theory has proved that the ratio of the mean square between groups to the mean square within groups is a statistic that obeys the F distribution. Comparing MSA with MSE, the required F-test statistic is obtained, as shown below.

According to the given significance level α, check the F distribution table to determine the critical value $(k-1, n-k)$. According to the given significance level α, numerator (mean square between groups) degrees of freedom $= k-1$, denominator (mean square within groups) degrees of freedom$= n-k$,find $(k-1, n-k)$ to determine the corresponding critical value. The specific operations are given in (6)-(11).

$$\overline{x_i} = \frac{\sum_{j=1}^{n_i} x_{ij}}{n_i} \tag{5}$$

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i} x_{ij}}{n} = \frac{\sum_{i=1}^{k} n_i \overline{x_i}}{n}, \tag{6}$$

$$\mathrm{SST} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \bar{\bar{x}})^2, \tag{7}$$

$$\mathrm{SSE} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \bar{\bar{x}}_i)^2, \tag{8}$$

$$\mathrm{SSA} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(\overline{x_i} - \bar{\bar{x}})^2 = \sum_{i=1}^{k} n_i(\overline{x_i} - \bar{\bar{x}})^2 \tag{9}$$

$$\sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \bar{\bar{x}})^2 = \sum_{i=1}^{k} n_i(\overline{x_i} - \bar{\bar{x}})^2 + \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \overline{x_i})^2 + \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \overline{x_i})^2, \tag{10}$$

$$F = \frac{\mathrm{MSA}}{\mathrm{MSE}} \sim F(K-1, n-k), \tag{11}$$

According to the given significance level α, check the F distribution table to determine the critical value $(k-1, n-k)$. According to the given significance level α, numerator (mean square between groups) degrees of freedom $= k-1$, denominator (mean square within groups) degrees of freedom$= n-k$,find $(k-1, n-k)$ to determine the corresponding critical value.

According to the calculated value F of the test statistic, compare it with the critical value $(k-1, k-n)$ obtained from the look-up table, and make a statistical decision. If $F > F_{\alpha}$, the null hypothesis is rejected, that is, the hypothesis of $\mu_1 = \mu_2 = \ldots \mu_i = \ldots = \mu_k$ is not true, indicating that the influence of factors on the experimental results is greater than the random error on the experimental results. If $F < F_\alpha$, the null hypothesis cannot be rejected , There is insufficient evidence to prove that the influence of factors on the experimental results is greater than the influence of random errors on the experimental results. When making statistical decisions, you can also directly use the output P value in the analysis of variance table to compare with the significance level to draw conclusions.

The results of factor analysis of variance show that the performance of various topics with different topics is significantly different in the difficulty value . Therefore, when selecting the difficulty that affects the reading of English texts, the topic should also be regarded as having a strong correlation with the actual difficulty value. The factor of is considered in the characteristic value that affects the difficulty of English reading.

Table 2:Factor Analysis of Variance

Variable name	Variable	Sample Size	Mean Standard	Deviation	F	p
Correct Rate	Application	33	0.763	0.038	13.687	0.002**
	Narrative	47	0.664	0.078		
	Explanatory Text	45	0.545	0.006		
	Total	125	0.649	0.100		

2.2. Weight Determination.

Among the many eigenvalues, we finally selected the eigenvalues with excellent properties such as the symbolic symbol ratio, sentence complexity, word ambiguity, multi-syllable word ratio, and difficult word ratio. Based on the above eigenvalues, we constructed the initial The matrix has m evaluation objects and n evaluation indicators.

First select the range standardization to process the data. The formula is about positive indicators and negative indicators.

Perform non-quantitative processing on standardized data to eliminate the influence of dimensions on the data, and calculate the proportion of the characteristics of the i-th data under the j-th index. Entropy calculation, calculate the entropy of the j-th term. Calculate the effective value of information. Determine the weight of the j-th index. The weights such as the ratio of symbolic characters, sentence complexity, word polysemy, multi-syllable word ratio, and difficult word ratio are shown in the figure.

After entering the correlation matrix, we calculate the information entropy, information effective value and weight and other data.

It can be seen from the figure that among the five eigenvalues of symbolic symbol ratio, sentence complexity, word ambiguity, multi-syllable word ratio, and difficult word ratio, the weight of sentence complexity eigenvalue is the largest 0.2414387. Followed by the ratio of symbolic characters, the ratio of difficult words, the polysemy of words, and the ratio of polysyllable words, which accounted for 0.229417, 0.2145756, 0.1840796, and 0.1304885 respectively.

Calculate the comprehensive score F, and visualize the data, the F score calculation formula is as follows. The specific operations are given in (12)-(18).

$$r_{ij} = \frac{x_{ij} - x_{jmin}}{x_{jmax} - x_{jmin}}, \mathrm{i} = 1,2,3\ldots, \mathrm{m}; \mathrm{j} = 1,2,3\ldots, \mathrm{n}, \tag{12}$$

$$r_{ij} = \frac{x_{jmax} - x_{ij}}{x_{jmax} - x_{jmin}}, \mathrm{i} = 1,2,3\ldots, \mathrm{m}; \mathrm{j} = 1,2,3\ldots, \mathrm{n}, \tag{13}$$

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}, \tag{14}$$

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad \mathrm{k} = \frac{1}{\ln \mathrm{m}}; \tag{15}$$

$$g_j = 1 - e_j, \tag{16}$$

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j}, \quad j = 1,2,3,\ldots, n \tag{17}$$

$$F_i = \sum_{j=1}^{n} w_j p_{ij}, \quad i = 1,2,3\ldots, m, \tag{18}$$

Table 3: Each Eigenvalue Weight

	TTR	Sentence Complexity	Word Polysemy	Multi-syllable Word Ratio	Difficult Word Ratio
w_j	0.229417	0.2414387	0.1840796	0.1304885	0.2145756

3. Calculation Method and Verification

First of all, we need to define the symbols in advance to facilitate reading later.

Knowing the weights, we calculate the comprehensive score of each set of test papers. It can be seen that the score of L is the largest, and the correct rate of the corresponding test paper is also the lowest, indicating that the article is difficult to read. A test with a lower score indicates that the article is less difficult and has a higher accuracy rate.

After calculating the result, we need to perform a certain analysis on the error of the data to determine whether the construction of the model conforms to the real situation.

We need to standardize the score calculated by AND, as shown in the following formula.

Then we need to calculate the distance between the optimal value and the worst value of each unit index

Calculate the relative closeness of each index to the optimal value, the formula is as follows: The specific operations are given in (19)-(22).

The operation is shown in the figure. From the figure, we can see that the model prediction value has a higher degree of fit with the actual value, and the error is small. The feature value selection and weighting of this model are more reliable and can be used to predict English articles The difficulty of reading.

$$Z_{ij} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^{m} Y_{ij}^2, i}} = 1,2\ldots. m; j = 1,2\ldots n \tag{19}$$

$$D_j^* = \sqrt{\sum_{j=1}^{n}(Z_{ij} - x_j^*)^2}, i = 1,2....m, \quad (20)$$

$$D_i^0 = \sqrt{\sum_{j=1}^{n}(Z_{ij} - x_j^0)^2}, i = 1,2....m, \quad (21)$$

$$C_i^* = \frac{D_i^0}{D_i^0 + D_j^*}, i = 1,2....m, \quad (22)$$

Table 4: All Scores

Test	A	B	C	D
Mark	0.025329573	0.30750955	0.6560552	0.566974003
Test	E	F	G	H
Mark	0.140536907	0.347312417	0.762401206	0.740299887
Test	I	J	K	L
Mark	0.065595093	0.293118041	0.601343311	0.856182639

Text readability is one of the indirect indicators to measure the quality of academic writing. Vocabulary complexity and syntactic complexity, as the two key language indicators for written language output, can effectively predict the quality of academic writing. In our research, in view of the sentence structure composed of words and sentences, this paper constructs a comprehensive evaluation model by using the method of calculating the score of the article and the value of the Pearson correlation coefficient of many characteristic values and the entropy method. To measure the readability of English text. It focuses on the impact of vocabulary complexity and syntactic complexity on text readability, and tries to make timely suggestions for academic English writing teaching. Compared with traditional expert manual evaluation, this model evaluation has the following advantages:

The evaluation rules and standards are clearer and it can be described quantitatively.

The evaluation rules have better scalability and can be learned and modified adaptively based on big data;

The result is shown in Figure 2. It can significantly improve the efficiency of evaluation and save time, manpower, material resources and other resources for compiling English reading materials. It should be pointed out that there are few researches currently linking text readability with vocabulary complexity and syntactic complexity. This article only discusses the relationship between some indicators of vocabulary and syntactic complexity and text readability, which has certain limitations. This method also has certain limitations for large-scale applications. For example, the required data preparation is too complicated and cumbersome, and the evaluation performance can be further improved by continuing to increase the types of features.

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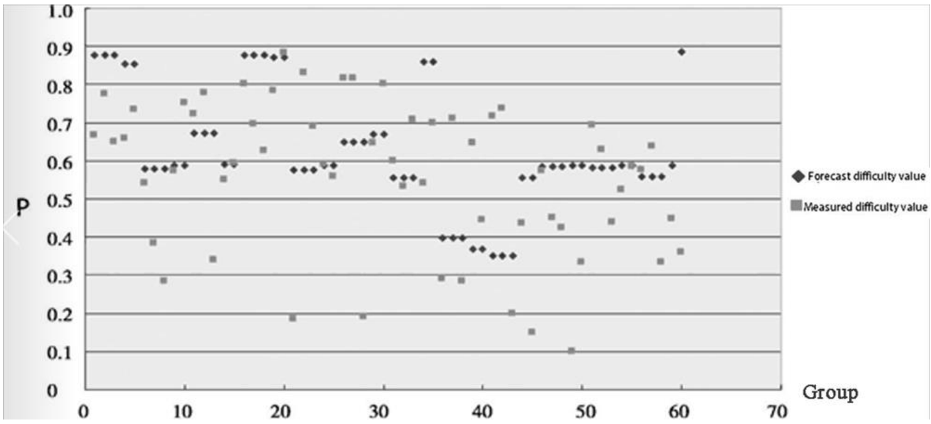

Figure 2:Forecast and Actual Model Diagram

4. Results and Generalization

In this paper, in the selection of eigenvalues that affect reading difficulty, the variables that are more significant in the model are selected as alternative variables, and input into the model based on the importance ranking, and then according to the overall effect of the variable combination, a model is established, which improves the accuracy of prediction. And this paper uses a variety of mathematical software in the process of solving the model to make the results of the model more accurate. However, in the selection of research objects in this paper, due to the selected research materials, the reading comprehension questions of the English test (AD section) of the National Unified Examination for General College Admissions in 2018-2019 (here is called the college entrance examination), the correct rate of the questions may also be affected. topical influence. Moreover, the psychological factors of the test takers are not considered, so the following improvements are made to the model:

The data selected in this article comes from the 2018-2019 college entrance examination English reading comprehension text and its score rate. The score rate of each question will also be affected by the test taker's personal background, psychological factors, etc., but as a high-level test topic, personal factors should be avoided influence. If the model is to be used to assess the reading difficulty of English texts in order to use the texts as language test materials for the appropriate level of difficulty, the test taker factor is one of the influencing factors that has to be considered. When the model is applied to select language test materials of appropriate difficulty, the psychological factors of the test taker should also be considered. There are many methods for measuring the psychological load of the test taker, which are generally divided into three categories: subjective perception measurement, external performance measurement and physiological measurement. condition. Because physiological state measurement is usually immediate and continuous, and is easily affected by environmental factors and the physical state of the subjects, subjective perception measurement and external performance measurement are usually used to calculate the influence of psychological factors on the difficulty of text reading. Subjective perception generally uses scales as measurement tools, NASA-TLX (commonly used scale NASA Task Load Index Scale) developed by Hart & Staveland (1988), similar to the Likert scale, including 6 dimensions: Mental needs (to complete tasks mental effort expended), physical demands (physical effort required to complete the task), time demands (the time pressure felt), effort level, performance (score of one's own performance), and frustration. The commonly used psychological load indicators for external performance measurement are speed (or time spent) and accuracy (or number of errors).

This model can not only be used to judge the reading difficulty of English articles, but also can be applied to other languages (such as Chinese, which is very different from English) to predict the reading difficulty of texts in other languages. The following is an example of Chinese:

The selected research materials are the reading comprehension texts in the 4 sets of C.TEST (AD level) examination papers in 2019-2020, and the accuracy of these reading comprehension questions is taken as the difficulty value of the text, because these questions are used for formal examinations. question, so the actual difficulty parameter of the text is the real value that has been obtained.

Select 9 factors that significantly affect the reading of Chinese texts, namely: number of words in the article, number of Chinese character parts, number of sentences in the article, average sentence length, proportion of function words, proportion of B-level words, C-level words proportion, super-class words proportion, article theory The Pearson coefficient between the value of these factors and the actual difficulty is obtained by correlation analysis. Then, the entropy weight method is used to assign weights to the above eigenvalues, and the relevant scores are calculated. The distance calculation is performed on the optimal and worst values by the Topsis method. The calculation results are compared with the actual value of the fitting degree, and the fitting degree is observed. If the fitting degree is higher, the model is suitable; The extraction and entropy weight determination are continuously optimized to achieve the best fit.

5. Conclusion

This paper proposes an English text readability measurement model based on the comprehensive evaluation model, and has achieved certain research results. However, due to time constraints, there are still some follow-up work, which are worthy of our further study. Prospects for research work:

In the future, we may replace the comprehensive evaluation model with a new network structure with stronger learning ability, which can simplify the structure of the model and learn more local and global semantic information.

We can also consider incorporating syntactic number features when characterizing sentences to emphasize the syntactic structure of the chapter and strengthen the representation of chapter features. In some related tasks, such a method can improve the performance of the model, so this method can be tried. Therefore, in the future, this model, which has gradually matured in English, can be extended to other languages, such as Chinese, which is quite different from English.

It should be noted that few studies have linked text readability to lexical complexity and syntactic complexity. This paper only discusses the relationship between some indicators of lexical and syntactic complexity and text readability, and there are certain

limitations. This method also has certain limitations for large-scale applications, such as the required data preparation is too complicated and cumbersome, and the evaluation performance can be further improved by continuing to increase the types of features in the future.

However, the existing research results can start from the lexical and syntactic structure level in more detail, and provide reference suggestions for academic English writing and teaching. For future text readability research, it is necessary to incorporate deep-level influencing factors such as discourse on the basis of lexical and syntactic complexity, and develop a more complete readability formula to determine the difficulty of text reading, and more good to help scholars improve the quality of their papers.

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